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METAMODELS AS INPUT OF AN OPTIMIZATION ALGORITHM FOR SOLVING AN INVERSE EDDY CURRENT TESTING PROBLEM

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Abstract

A new mean of solution of eddy current testing (ECT) inverse problems is presented herein. The aim is to characterize a defect within a generic work piece by inverting an ECT signal in a short time (less than 5 s on a standard PC). The inverse problem is solved using Particle Swarm Optimization (PSO). As inputs of this algorithm, a metamodel is used in order to reduce the computation load and to contribute to building up a fast ECT inverse method. It is tested on a number of synthetically generated data, the chosen work piece being a tube. It is also tested on two sets of measured data. The proposed method shows good accuracy, satisfactory speed, and provides additional information besides the inversion results, which highlights possibly indeterminate cases. So it is useful as well for decision analysis.

In order to create the metamodel, an adaptive database is generated [1]. This database concentrates more points when the output variations are fast. Points in the database tend to be homogeneously distributed in the output space, not in the input space. Then, an interpolation using radial basis function (RBF) with a thin plate spline (TPS) kernel function is applied. RBF interpolation is chosen because it is accurate, fast, and it deals with vector data.

PSO is a metaheuristic based on swarm intelligence [2]. Its principle, as a reminder, is to set particles in the input space with a rather homogeneous distribution. For each one, a cost function is computed, and the particles randomly move towards directions corresponding to local bests. By sharing information, the particles finally converge to the global minimum of the cost function. This optimization method requires many forward simulations that are here replaced by the metamodel. It makes the optimization much faster. Consequently, the accuracy of the optimization is directly related to the accuracy of the metamodel.

During the creation of the metamodel, the generation of the adaptive database is a crucial step. Depending on the chosen norm, the database is more accurate for large defects (normalization by a fixed value, denoted as norm 1) or for small defects (normalization by the norm of tested signal, denoted as norm 2). In this study, databases are generated for both norms 1 and 2, from which metamodels are created and used with the inverse method to highlight these differences.

A result on measured data is shown in Figure 1. This test case corresponds to the defect GI10 of the 2008 ECT benchmark [3], characterized by two parameters. It is an internal groove of 1 mm width with a depth of 10 % of the tube thickness. The circles correspond to the true parameters and the squares to the maxima of the likelihood obtained by PSO. The grey surfaces are the level lines of the likelihood function, normalized to 1. In this example, the width of the defect in the database is in the interval [0.1 10] mm and its depth in [10 90] %. PSO results with the databases generated with the norm 1 and norm 2 are plotted on the right and left of Figure 1, respectively.

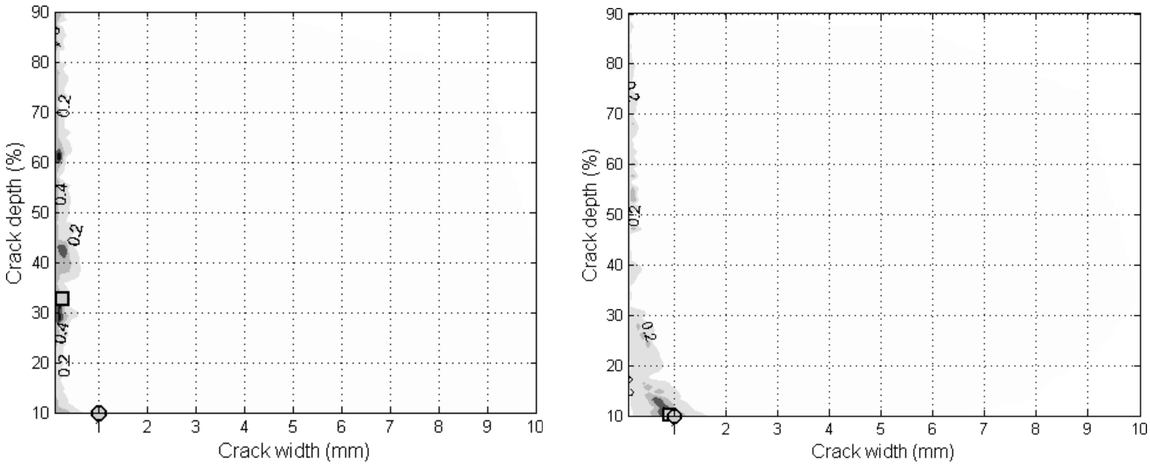

Figure 1. Level lines of the likelihood function obtained by PSO on the measured test case with an adaptive database generated according to norm 1 (left) and norm 2 (right). The circles point to the true parameters and the squares to the maximum of likelihood.

This result exemplifies important features of the inverse method. First, the inversion highly depends upon the metamodel. One must keep in mind that these two results have been obtained with the same tunings for PSO. As expected, the result with the norm 2 is better. Actually, this norm emphasizes small cracks, which GI10 is. Moreover, the level lines of the likelihood function yield some information about the reliability of the result.

The inverse method has also been tested on 200 simulated cases. As expected, the results with the norm 1 are better for signals simulated in the presence of large cracks, and the norm 2 is better for small cracks. However, whatever the norm chosen, the mean accuracy is satisfying for the whole testing and the developed method is very promising.

To conclude, an efficient inverse method for ECT inverse problems has been presented. It provides fast results (order of magnitude of 1 second) with an approximation of the likelihood function. However, the end-user should be aware that during the training step of the method, the creation of the database has to be fitted to the type of cracks which he/she wants to characterize. A norm combining the two normalizations could be considered so as to deal with more types of defects. Also, this method should be now tested on problems in higher dimension.

References

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